The Comparative Study of Deep Learning Neural Network Approaches for Breast Cancer Diagnosis

https://doi.org/10.3991/ijoe.v19i06.34905

Haslinah Mohd Nasir[1(✉)], Noor Mohd Ariff Brahin[1], Suraya Zainuddin[1], Mohd Syafiq Mispan[1], Ida Syafiza Md Isa[1], Mohd Nurul Al Hafiz Sha'abani[2]
[1]Universiti Teknikal Malaysia Melaka, Melaka, Malaysia
[2]Universiti Tun Hussien Onn Malaysia, Johor, Malaysia
haslinah@utem.edu.my

Abstract—Breast cancer is one of the life-threatening cancer that leads to the most death due to cancer among women. Early diagnosis might help to reduce mortality. Thus, this research aims to study different approaches to the deep learning neural network model for breast cancer early detection for better prognosis. The performance of deep learning approaches such as Artificial Neural Network (ANN), Recurrent Neural Network (RNN) and Convolution Neural Network (CNN) is evaluated using the dataset from the University of Wisconsin. The findings show ANN achieved high accuracy of 99.9 % compared to others in detecting breast cancer. ANN can deliver better results with the provided dataset. However, more improvement is needed for better performance to ensure that the approach used is reliable enough for early breast cancer diagnosis.

Keywords—breast cancer, early diagnosis, deep learning, prognosis, neural network

1 Introduction

Breast cancer is one of the most common cancers in women that contributes to the most death due to cancer. Therefore, early detection is crucial as doctors may provide early treatment to reduce cancer mortality. The tumor sizes and how far it is spread are the main factors of their treatment and survival chances [1]. The pathologist is practically responsible for examining any cancerous tumor by testing the tissue sample to detect whether it is a noncancerous or cancerous tumor. Generally, there are two types of cancerous tumors; malignant and benign [2].

More researchers studied various methods for early-stage screening. One of the approaches highlighted is detection through malignant growth information. In current technology, Machine Learning strategy has become a mainstream instrument for clinical analysis. Utilizing Artificial Intelligence (AI) and information mining strategies has changed the procedure of malignant growth for diagnosis and prognosis [3].

Preliminary research on breast cancer prediction using machine learning such as Logistic Regression Algorithm, Support Vector Machine (SVM), Kernel Nearest Neighbor (KNN) and many more have been done. This research has become the foundation of this research. The machine learning approach was proven to perform well in breast cancer detection.

Naji et al. compared the machine learning approach of five different algorithms and found that SVM outperformed other classifiers with an accuracy of 97.2% [4]. Other research by Vaka et al. employed machine learning techniques for the early detection of breast cancer. The dataset from M. G Cancer Hospital & Research Institute, Visakhapatnam, India, was utilized for this research. They found that their proposed approach performs better than the existing machine learning with 97.21% accuracy [5]. While research by Rane et al. shows the comparison of machine learning algorithms with different data mining algorithms. The best model performance is embedded into their proposed system for the patient's breast cancer diagnosis in the website platform [6].

Machine learning is best for small data. It gave better results for the linear data. Machine learning is divided into three types; supervised machine learning, unsupervised machine learning and reinforcement machine learning. However, deep learning is the solution for better classification results for extensive data. Deep learning is a sub-field of machine learning where the algorithm is trained without supervision, called unsupervised learning [7].

A comparison study of different deep learning models by Shahidi et al. has been done using the histopathology image dataset of breast cancer. The study includes pre-processing, data augmentation and deep learning methods to evaluate the model performance of binary, four and eight classifications. They found that deep learning models are suitable for high-quality histopathological images, but there are challenges to acquiring high-resolution images [8].

Another research by Aljuid et al. applied medical image analysis techniques through computer-aided diagnosis using deep learning networks and transfer learning. The dataset was acquired from BreakHis for breast cancer classification. The results show a promising technique with up to 97.81% average accuracy for the ResNet approach of deep neural networks [9].

Multi-class classification of breast cancer abnormalities was applied to the customized dataset using CBIS-DDSM and UPMC. Convolutional Neural Network and transfer learning ResNet 50 models were developed to classify various abnormalities. The results show that the proposed method achieved 88% accuracy in abnormalities classification regarding its masses, calcifications, carcinomas and asymmetry mammograms [10].

Based on the literature survey, this research compares a few deep learning neural network approaches using the Wisconsin Diagnostic Breast Cancer (WDBC) dataset. In addition, the performance of each model was evaluated to show the comparison analysis.

2 Methodology

The methodology is divided into four stages, as shown in Figure 1. It starts with data acquisition and continues to the data processing stage. Then, the model is built in stage two of the working model before the classification stage. Lastly, the result from all the classifiers involved will be analyzed to decide which method has better accuracy and high performance. All the process was done based on python programming in Spyder software.

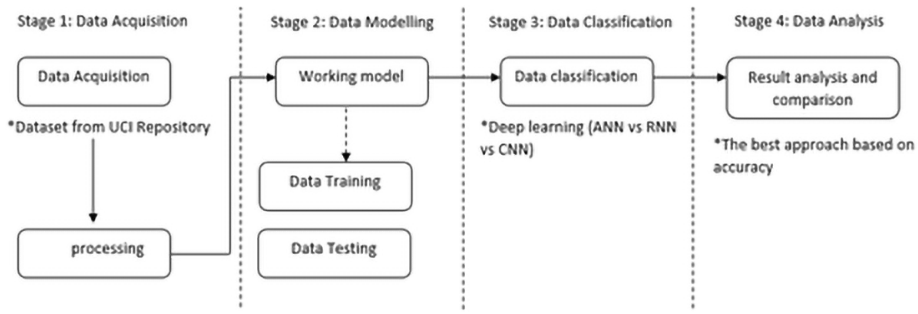


Fig. 1. Proposed methodology

2.1 Stage 1: data acquisition

The research utilizes a well-known dataset of breast cancer taken from the UCI Repository, Wisconsin Diagnostic Breast Cancer (WDBC) data set from the University of California based on two conditions benign (B) and malignant (M) tumours. The dataset comprises 357 benign and 212 malignant datasets with 30 features for each image, as shown in Figure 2. In contrast, the summary of the resulting dataset from the repository is shown in Table 1 [11].

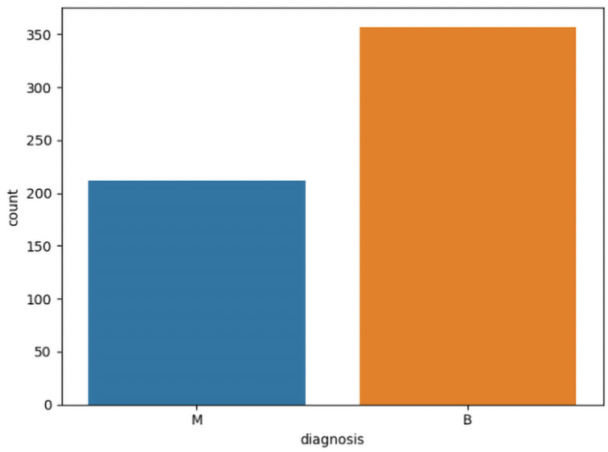


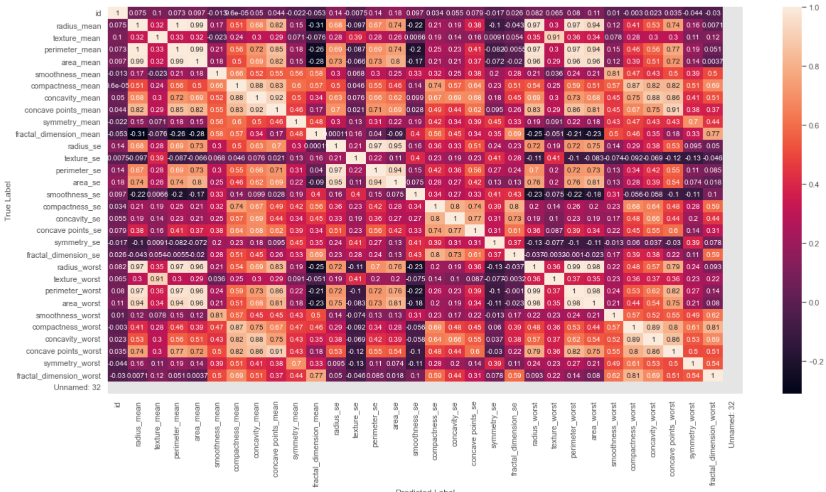
Fig. 2. Number of Malignant (M) and Benign (B) of UCI dataset

Table 1. The details of dataset from UCI repository

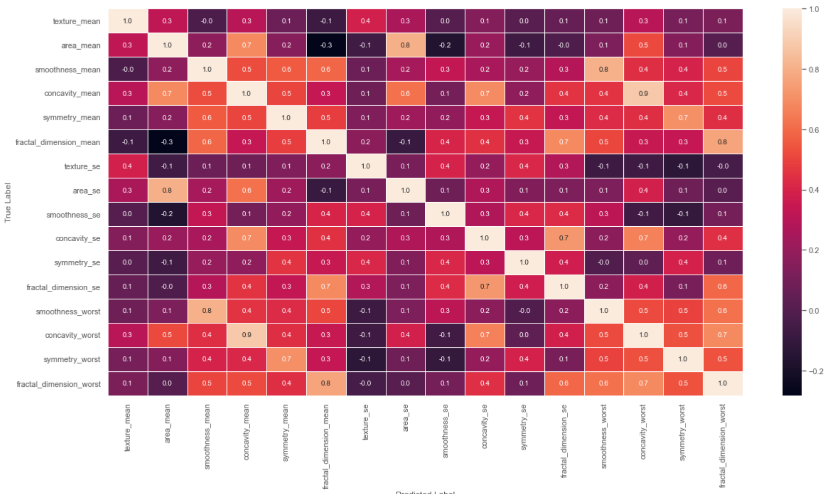
	Number of Sample	Accuracy (%)
Training data	403	97
Testing data	166	86
Validation data	75	100

According to Table 1, 569 benign and malignant patient datasets were provided for training of diagnostic data, 166 from the dataset were used for testing data, and the accuracy is about 97%. An additional 75 data were provided to validate the diagnostic system, and the accuracy was achieved 100%. This data is needed prior to this research to ensure that the proposed method can provide high accuracy in real applications.

In data processing analysis, feature extraction by removing unwanted data using the cross-validation approach is used to smooth the classification with the best accuracy later. Heatmap plot is one of the feature selection techniques that have been used to enhance classification performance. The correlation between the actual and predicted variables can be identified through the heatmap plot. The higher the correlation value, the higher the correlation between two variables. Based on the heatmap plot shown in Figure 3a, a few features were not correlated, and those can be removed. Figure 3b shows the heatmap plot after removing uncorrelated features.



(a)



(b)

Fig. 3. Heatmap plot before (a) and after (b) uncorrelated features removal

The heatmap plot is used to visualize the correlation between the features in high-dimensional space. In addition, it helps to ensure that the classification model can produce high prediction accuracy. Figure 4 presents the cross-validation of the selected features from the heatmap plot for five folds cross-validation. The figure plotted shows the five folds cross-validation to assess the difference in the performance. It can be clearly seen that selected features for five folds have high accuracy and can be utilized for better classification.

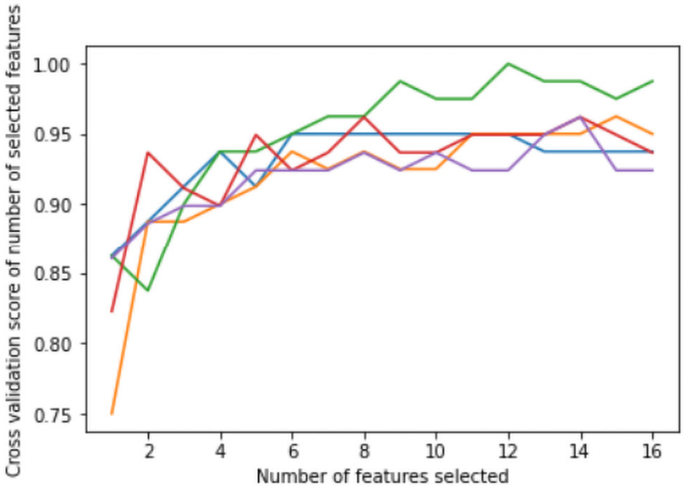


Fig. 4. Cross validation of selected features

After removing the unwanted data, Principle component analysis (PCA) was utilized for feature extraction. PCA is the method that can reduce the dimensionality of data to make the model prediction more accurate by providing the high-significance data required [12]. The features of the dataset for classification are selected through three principal components. Figure 5 interprets the correlation of the extracted features with the principal components. This step reduces the dimensionality of the dataset for diagnosing breast cancer.

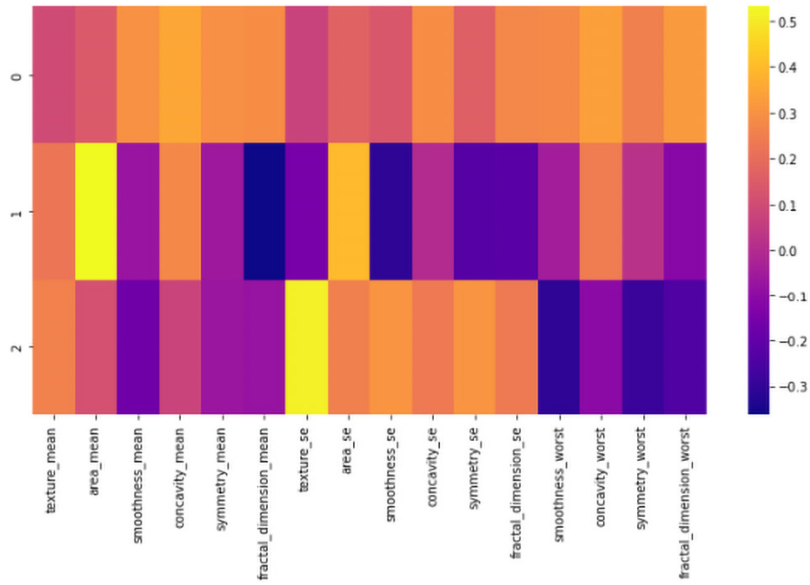


Fig. 5. Correlation of extracted features with the principal component

2.2 Stage 2: data modelling

At this stage, this research creates data modelling based on the various types of deep learning neural network approaches that can predict breast cancer conditions based on the given dataset. The dataset will be divided into two parts; training and testing data. 75% of the dataset (called training data) will be used to model the neural network algorithm, while another 25% of the dataset (testing data) will test the proposed model's performance.

Deep learning neural networks are the functional unit of deep learning that work like human biological behaviour. The input data is processed into different layers of artificial neurons before producing the desired output [13]. There are three different approaches to the neural network will be compared in this research, Artificial Neural Network (ANN), Recurrent Neural Network (RNN) and Convolution Neural Network (CNN). Recently, researchers have been more likely to apply a machine learning approach to predict breast cancer. However, this paper will focus on these three neural network approaches as they can produce better performance and avoid overfitting issues. Figure 6 shows the general infrastructure of deep learning neural network for a basic understanding of the workflow of neural networks.

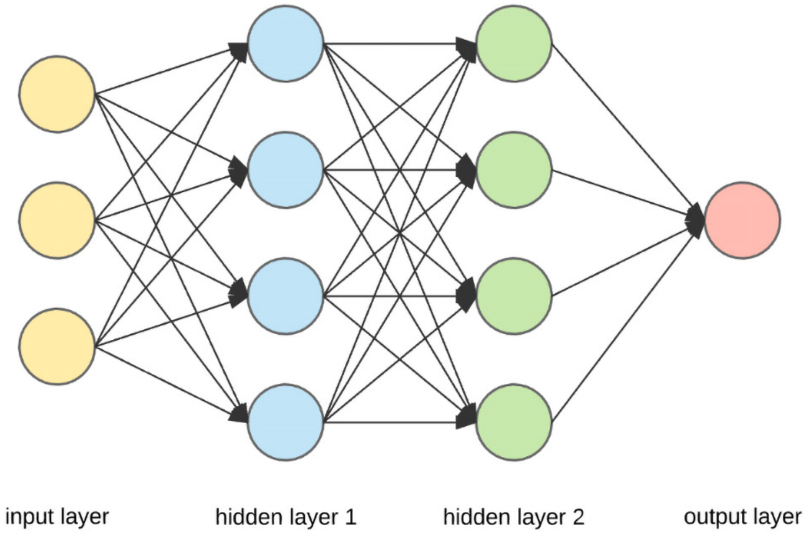


Fig. 6. General infrastructure of neural network

Neural network modelling consists of hidden layers with Rectified Linear Unit (ReLu) activation functions and sigmoid for the input dataset. Adam optimizer is used for all three neural network models with a 0.0005 learning rate. Adam algorithm is based on the adaptive estimation of the ordering moments, where it is computationally efficient with little memory requirement. In addition, it is suitable for large data solutions [14].

2.3 Stage 3: data classification

The model using three different neural network algorithms will be compared based on their testing data. The best model provides high accuracy and will be identified as the most predictive algorithm for the detection of breast cancer.

ANN is known as Feed-Forward Neural Network due the inputs are processed in the forward direction, which learns from the certain weights of the activation function. In comparison, RNN has a recurrent connection on the hidden state compared to ANN. This feature is the function to capture the sequential information of the input data while making predictions. For CNN, it uses filters so-called as kernels to extract the features from the input data during convolution operation, and it is best for image processing. However, these three neural network approaches will be utilized in this research to identify breast cancer diagnosis using tabular data from the Wisconsin dataset.

2.4 Stage 4: data analysis

At this stage, the best performance of the neural network model will be presented based on the accuracy achieved. The analysis results will be shown and compared for better visualization of which approaches are better for breast cancer diagnosis.

The confusion matrix is used to evaluate the performance of the classification model. The confusion matrix helps give the output of Recall value, testing accuracy, precision value, and F1-Score [15]. It consists of 4 different combinations of predicted and actual results: True Positive, False Positive, False Negative and True Negative.

3 Results and discussion

In the feature extraction stage, 16 of 30 features have been extracted from the UCSI dataset. The features significantly correlate to ensure the prediction achieves high accuracy using a deep learning neural network. Figure 7 interprets the variance ratio of the dataset.

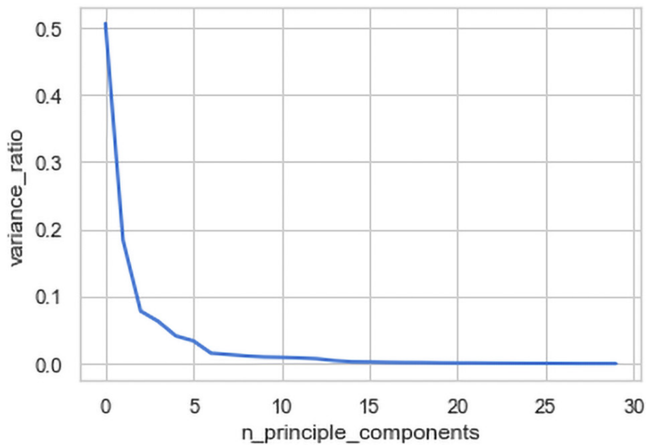


Fig. 7. Explained variance ration of dataset

As mentioned in the methodology, the dataset is divided 75:25 training ratio. The number of epochs for each neutral network differs depending on the learning model to avoid overfitting or under-fitting.

3.1 Artificial Neural Network (ANN)

ANN is modelled with six layers. ReLu and sigmoid activation functions were used for model training to perform better. Figure 8 depicts the ANN model performance based on model loss and accuracy.

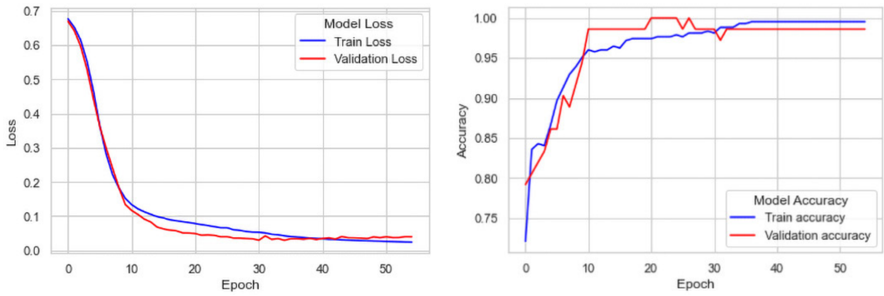


Fig. 8. ANN Model loss and accuracy

The model is trained with 100 epochs, but as seen from Figure 8, the model is generalizing well enough on the dataset. The validation and accuracy are stable at 50 epochs, and the difference between these two is narrow, which means that the model is not overfitting or underfitting. This model's training and validation loss scores decreased to 0.0242 and 0.0397, respectively. At the same time, training and validation accuracy achieved 0.9953 and 0.9861, respectively.

3.2 Recurrent Neural Network (RNN)

RNN modelling of the breast cancer dataset utilized the linear activation function approach, which is a straightforward model prediction. The model runs the training with 200 epochs, and the model loss is presented in Figure 9. For RNN, the epoch is more than the ANN and CNN as it requires more time to pass all the training datasets through the ADAM learning algorithm.

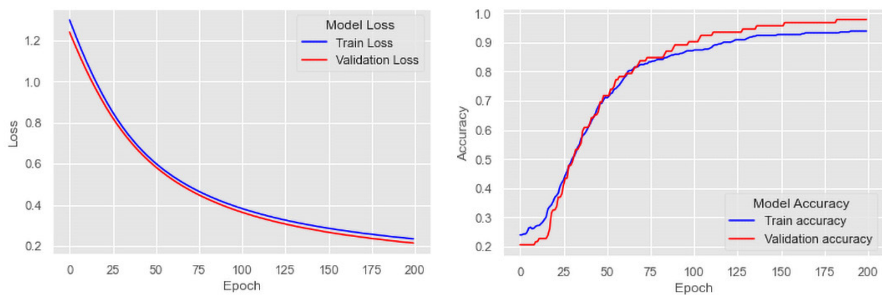


Fig. 9. RNN Model loss and accuracy

The calculated training accuracy of this model achieved 0.969. At the same time, the model loss is 0.141. However, the graph shows the possibility of an under-fitting issue with the same parameter used for another model. It can be seen that the validation accuracy is higher than the training accuracy. The division of training, test and validation data affects the under-fitting issue. It can be solved by carefully dividing the training, test and validation data. In this paper, since comparing these models uses the same parameter, no changes will be made to ensure a fair comparison.

3.3 Convolution Neural Network (CNN)

CNN is the most distinctive deep learning approach, especially in image processing. Thus, the tabular data is converted into 3D data for a more straightforward interpretation of the CNN model. This CNN is modelled with two layers of convolution layer, two layers of max-pooling and one layer fully connected with ReLu and sigmoid activation at the output. As a result, training and validation loss is down to 0.0351 and 0.1003, respectively, while the training and validation accuracy achieved 0.9883 and 0.9790, respectively. Figure 10 shows the CNN model loss and accuracy with 100 epochs.

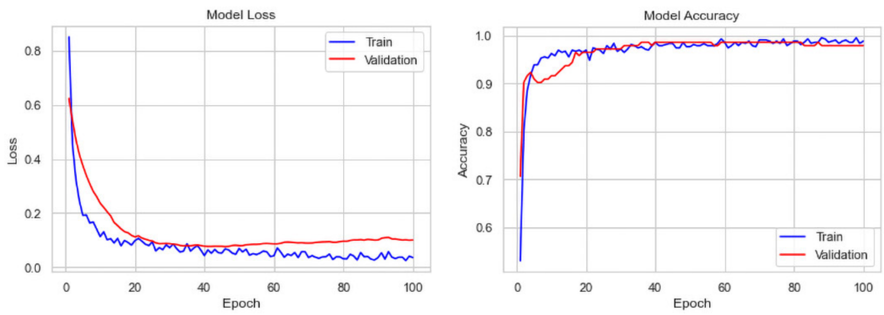


Fig. 10. CNN model loss and accuracy

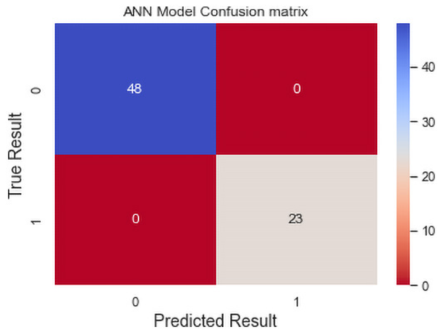
3.4 Analysis

In order to compare the performance of each deep learning neural network model, the confusion matrix was used. The evaluation measurement can be seen in Table 2. The evaluation parameter is based on the model confusion matrix's testing accuracy, precision value, Recall value and F1-Score.

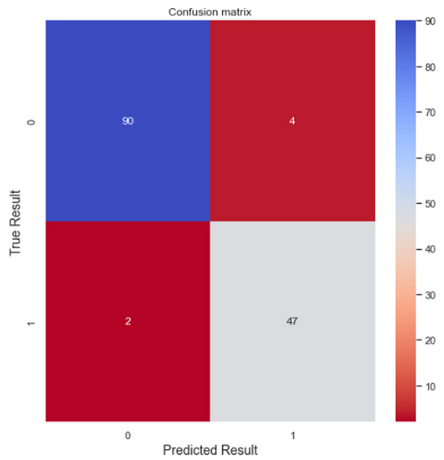
Table 2. Comparison of performance of ANN, RNN and CNN

Evaluation Parameter	Deep Learning Neural Network Model		
	ANN	RNN	CNN
Accuracy (%)	99.9	95.8	97.9
Precision	0.99	0.946	0.981
Recall	0.99	9.938	0.962
F1-Score	0.99	0.949	0.971

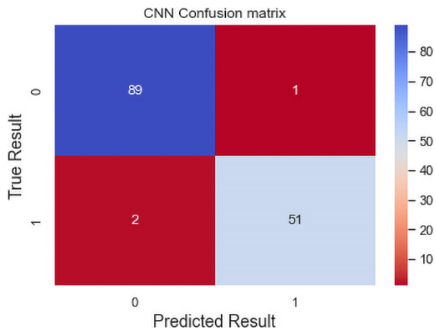
Based on Table 2, ANNs have portrayed better performance compared to the other models. The accuracy of the ANN model is achieved at 99.9% compared to CNN at 97.9%. The confusion matrix from this analysis is shown in Figure 11. True Positive is the combination of 1 1 for both predicted and actual results; 1 0 and 0 1 depict False Negative and False Positive, respectively. While the combination of 0 0 denotes the True Negative.



a) ANN model



b) RNN model



c) CNN model

Fig. 11. Confusion matrix for each model

ANN is better than another model in terms of analysis performed using a confusion matrix. It almost achieved 99.98%, where it successfully predicts the data based on the training model with the same epoch of the CNN model.

4 Conclusion

This research aims to propose a deep learning neural network model that fits with high accuracy, a breakthrough in technology for the early detection of breast cancer. Unfortunately, breast cancer awareness is lacking because innovation and studies were not run in parallel with the number of deaths in many years, which is a concern for most women. Therefore, artificial intelligence, specifically deep learning techniques, comes as a saviour who needs a small amount of human touch to utilize for early diagnosis.

Based on the analysis, the best algorithm that suits the breast cancer diagnosis model is Artificial Neural Network (ANN). Because of the nature of the algorithm itself, it used a different method for estimating the parameter, thus helping deliver better results.

However, more research should be done with a different dataset, such as an image or signal, for accuracy and performance comparison. A better result is comprised of unbiased prediction with lower variances. It is needed to be implemented in the actual application of cancer early detection from MRI or scanning. In addition, the hybrid with other techniques should be considered as it may help in the early diagnosis of cancer.

5 Acknowledgment

Thanks to Universiti Teknikal Malaysia Melaka (UTeM) for providing a project site to complete this research. Also, to the University of Wisconsin for making the dataset from the UCI Machine Learning Repository available for use in this research.

6 References

[1] Narod, S. A. (2012). Tumor size predicts long-term survival among women with lymph node-positice breast cancer. Current Oncology, 19(5): 249–253. https://doi.org/10.3747/co.19.1043
[2] Cooper, G. M. (2000). A molecular approach. 2nd edition. Sunderland (MA): Sinauer Associates. The Development and Causes of Cancer.
[3] Kumar, Y., Gupta, S., Singla, R. and Hu, Y.–C. (2022). A systematic review of artificial intelligence techniques in cancer prediction and diagnosis. Arch Comput Methods Eng, 29(4): 2043–2070. https://doi.org/10.1007/s11831-021-09648-w
[4] Naji, M. A., Filali, S. E., Aarika, K., Benlahmar, E. H., Abdelouhahid, R. A. and Debauche, O. (2021). Machine learning algorithms for breast cancer prediction and diagnosis. Procedia Computer Science, 191: 487–492. https://doi.org/10.1016/j.procs.2021.07.062
[5] Vaka, A. R., Soni, B. and Reddy, K. S. (2020). Breast cancer detection by leveraging machine learning. ICT Express, 6(4): 320–324. https://doi.org/10.1016/j.icte.2020.04.009
[6] Rane, N., Kanade, R., Sunny, J. and Devi, S. (2020). Breast cancer classification and prediction using machine learning. International Journal of Engineering Research & Technology, 9(2): 576–580. https://doi.org/10.17577/IJERTV9IS020280
[7] Priyanka, K. S. (2021). A review paper on breast cancer detection using deep learning. IOP Conf Series: Materials Science and Engineering, 1022: 012071. https://doi.org/10.1088/1757-899X/1022/1/012071
[8] Shahidi, F., Daud, S. M., Abas, H., Ahmad, N. A. and Maarop, N. (2020). Breast cancer classification using deep learning approaches and histopathology image: A comparison study. IEEE Access, 8: 187531–187552. https://doi.org/10.1109/ACCESS.2020.3029881
[9] Aljuaid, H., Alturki, N., Alsubaie, N., Cavallaro, L. and Liotta, A. (2022). Computer-aided diagnosis for breast cancer classification using deep neural networks and transfer learning. Computer Methods and Programs in Biomedicine, 223: 106951–106960. https://doi.org/10.1016/j.cmpb.2022.106951
[10] Mamode Khan, M. H., Jahangeer, N. B., Dullull, W., Nathire, S., Gao, X., Sinha, G. R. and Nagwanshi, K. K. (2021). Multi-class classification of breast cancer abnormalities using Deep Convolutional Neural Network (CNN). PLOS ONE, 16(8): e0256500. https://doi.org/10.1371/journal.pone.0256500
[11] Wolberg, W. H., Street, W. N., Heisey, D. M. and Mangasarian, O. L. (1995). Image analysis and machine learning applied to breast cancer diagnosis and prognosis. Analytical and Quantitaive Cytology and Histology, 17(2): 77–87.

[12] Hasan, M. M., Haque, M. R. and Kabit, M. M. J. (2019). Breast cancer diagnosis models using PCA and different neural network architectures, 2019 International Conference on Computer, Comunnication, Chemical, Materials and Electronic Engineering (IC4ME2), 1–4. https://doi.org/10.1109/IC4ME247184.2019.9036627
[13] Khuriwal, N. and Mishra, N. (2018). Breast cancer diagnosis using deep learning algorithm, 2018 International Conference on Advances in Computing, Communication Control and Networking (ICACCCN), 98–103. https://doi.org/10.1109/ICACCCN.2018.8748777
[14] Kingma, D. P. and Ba, J. (2015). Adam: A method for stochastic optimization. 3rd International Conference for Learning Representations, 1–15.
[15] Singh, P., Singh, N., Singh, K. K. and Singh, A. (2021). Chapter 5-Diagnosing of disease using machine learning. Machine Learning and the Internet of Medical Things in Healthcare, 89–115. https://doi.org/10.1016/B978-0-12-821229-5.00003-3

7 Authors

Haslinah Mohd Nasir received her Bachelor Degree in Electrical – Electronic Engineering (2008) from Universiti Teknologi Malaysia (UTM), MSc (2016) and PhD (2019) in Electronic Engineering from Universiti Teknikal Malaysia Melaka (UTeM). She had 5 years (2008–2013) experience working in industry and currently a lecturer in UTeM. Her research interest includes microelectronics, artificial intelligence and biomedical.

Noor Mohd Ariff Brahin received B. Eng Electrical – Electronic (Hons) from Universiti Teknologi Malaysia (UTM) in 2008. He had experience working in the semiconductor industry as a structural design engineer from 2008 until 2013. He is currently a teaching engineer in Universiti Teknikal Malaysia Melaka. His research interests include artificial intelligence, microelectronics and IC design.

Suraya Zainuddin is a lecturer in Faculty of Electrical and Electronic Engineering Technology (FTKEE), Universiti Teknikal Malaysia Melaka (UTeM). She received the Bachelor of Engineering (Electrical-Communication) from Universiti Teknologi Malaysia (UTM) in 2003, MSc in Telecommunication and Information engineering in 2015 and PhD in Electrical Engineering in 2020 from Universiti Teknologi MARA (UiTM). Her main research areas involved the studies in Multiple-input multiple-output (MIMO) radar, radar system and application, signal processing and radar detection.

Mohd Syafiq Mispan received B. Eng Electrical (Electronics) and M. Eng Electrical (Computer and Microelectronic System) from Universiti Teknologi Malaysia in 2007 and 2010 respectively. He had experience working in semiconductor industries (2007–2014). He obtained his Ph.D. degree in Electronics and Electrical Engineering from University of Southampton, United Kingdom in 2018. He is currently a senior lecturer in Universiti Teknikal Malaysia Melaka. His current research interests include hardware security, CMOS reliability, VLSI design, and Electronic Systems Design.

Ida Syafiza Md Isa received the PhD degree from the University of Leeds, U.K. in 2020, worked on energy efficient access networks design for healthcare applications. She is currently a Senior Lecturer in Universiti Teknikal Malaysia Melaka (UTeM), Malaysia. She has published several articles in this area. Her research interests include network architecture design, energy efficiency, network optimization, mixed integer linear programming and pt healthcare systems.

Mohd Nurul Al Hafiz Sha'abani is an electrical engineering lecturer at the Centre for Diploma Studies of Universiti Tun Hussein Onn Malaysia. He earned a bachelor's degree in Mechatronic Engineering and Master of Science in Electrical Engineering from Universiti Teknikal Malaysia Melaka. He is currently continuing his studies in doctorate at Universiti Tun Hussein Onn specializing in biomedical engineering. His research interest is in signal processing, robotics, artificial intelligence and smart system.

Article submitted 2022-08-25. Resubmitted 2023-02-24. Final acceptance 2023-02-24. Final version published as submitted by the authors.